Features Understanding for Contactless and Contact-Based Fingerprint Matching

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A contactless fingerprint is a novel approach to fingerprint recognition, that originated after the covid-19 pandemic because of hygiene issues. In contactless and contact-based fingerprint matching several patterns and features are used to study the ridge-valley patterns of the fingertip. So, the performance of a fingerprint-matching system depends on the feature extraction phase. Therefore, feature selection should be done cautiously. Over the period, numerous features and corresponding approaches have been developed for fingerprint recognition. Selecting one or more features is a crucial step in fingerprint identification, which depends upon the database and type of application (like military, commercial, etc.). Hence, the purpose of this study is to do a comprehensive assessment of the available features for matching contact-based and contactless fingerprints.

Keywords: Contact-based, Contactless, levels of features, minutia points, singular points, texture features, frequency feature, deep feature.

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1. Introduction

Fingerprints are impressions of the ridges and valleys of the fingertips, used in biometric systems to identify individuals. Fingerprint matching has been used for a long period in many fields like criminology, government documentation, and in many organizations as the identification tool for individuals. During COVID-19 this practice was stopped because of hygiene problems, and the need for contactless fingerprint scanning became essential. Contactless images have complications like light illumination, distance from the camera, camera resolution, etc. In contact-based images deformation from scanning devices and the elasticity property of human skin cause alteration in the fingerprint image. Therefore, matching contact-based and contactless fingerprint images depends on the type of features being used. Over time, many techniques based on different features and patterns have been developed to study the fingerprint. But then again selecting one or two among many approaches is a critical and vital step. The purpose of this review is to do a broad assessment of the available features and methods for fingerprint-matching techniques.

Fig. 1. The basic structure of fingerprint matching

Figure 1 illustrates the basic structure of contact-based and contactless fingerprint matching, where both images are preprocessed using enhancement and deformation correction. After pre-processing most important part is to extract features from the enhanced image. Features represent the basic discriminable information of the fingerprint. They can be handcrafted (manually extracted features) or deep learning-based (deep features). Based on the basic properties of ridges, features are classified in three orders: Level-1, Level-2, and Level-3. Level 1 involves the basic pattern of the ridges; Level-2 comprises the minutiae features. Level-3 works on the ridge's shape and pores [1]. For matching, fingerprints are compared roughly using four main approaches: Pattern-based, Feature-based (minutiae points), correlation-based, and deep learning-based matching. All four have their types of features which are studied and explored for fingerprint matching in this paper.

1.1 Feature Matching

Fingerprint matching is roughly categorized into four groups Pattern-based matching, Feature-based (minutiae points) matching, correlation-based matching, and deep learning models.

1. **Pattern-based matching** includes the comparison between the basic patterns of the fingerprints. The basic pattern can be the texture information, ridge shape, frequency, and local orientation. Which comprise level 1, level 3, and texture features. For matching using these features, the input image should be in proper alignment with the stored fingerprint, in the same position around the central point before comparison, to determine the match score.
2. **Feature-based matching** involves level 2 features (Minutiae features) for fingerprint recognition. Minutiae features are points that represent the basic ridge properties like ridge ending and ridge bifurcation. Minutiae point matching is also referred to as a point pattern matching method [1]. In this method, minutiae points are extracted from both the template and the query image, and matched minutiae pairings are used as the match score for fingerprint recognition.
3. **Correlation-based matching** comprises overlaying input images over the already stored template to compute the correlation for different alignments between pixels of both images [1]. Numerous transformed-based techniques have been explored like 2D discrete Fourier transform for phase-based fingerprint matching [2] and Fourier-Mellin transforms [3].
4. **Deep learning-based matching** has achieved promising results in fingerprint matching. deep neural networks are used for fingerprint matching. Here neural networks are trained to extract meaningful information as deep features. Though these methods have significant

performance improvement, to train a deep CNN model large database is required. Therefore, generating large databases is compulsory for deep learning methods. Table 1 represents the feature-matching methods with corresponding features and approaches.

Table 1. Features descriptions according to fingerprint matching method.

Features matching methods	Features	Approaches
Pattern-based matching	Texture, ridge shape, frequency, and orientation.	GLCM, DWT, CNN-based approach.
Features based matching	Minutiae points.	Rutovitz's crossing number, SIFT, and CNN-based approach.
Correlation-based matching	Frequency phase and amplitude.	Discrete Fourier transforms
Deep learning methods	Deep features	Deep neural network.

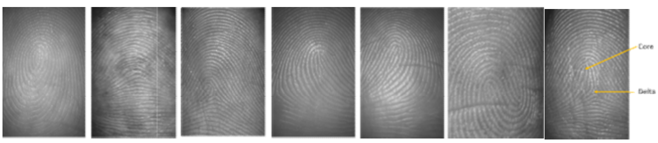
2. Fingerprint Features

The most significant part of the fingerprint recognition system is extracting features. Therefore, identification of what type of features are preferred for matching is essential. A fingerprint of the human fingertip is the print of the ridge-valley. Therefore, according to the ridge-valley pattern, and ridge's properties, features are classified into three levels. Level-1 (pattern of fingerprint), Level-2 (ridge ending/ bifurcation), and Level-3 (ridge's shape and pores) as presented in Figure 2 [1].

Fig. 2. (a) level-1 features, (b) level-2 features, and (c) level-3 features categorization [1].

2.1 Level 1

Fingerprint matching mostly has been done by comparing two fingerprints based on the basic pattern of the fingerprint impression. Level-1 features are based on the fingerprint's overall pattern and shape. They are also acknowledged as Singular points, and use larger image patches than minutiae points (approximately 1-5mm) [4]. There are three basic types of patterns in fingerprints: loop, whorl, and delta. According to them, a fingerprint can be classified into one of the six categories, defined by the grouping of loops and deltas. These categories are Arch, Tented-Arch, Whorl, Left-loop, Right-loop, and Double-loop, as illustrated in Figure 3 in contactless fingerprint images [4] [5] [6].



(a) (b) (c) (d) (e) (f) (g)

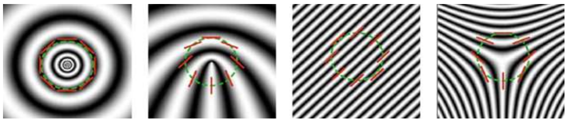
Fig. 3. (a) Whorl, (b) Arch, (c) Tented arch, (d) Right loop, (e) Left loop, (f) Double loop, (g) Core and delta [5] [6].

Loops have concentric staple or hairpin-shaped ridges and can be described as radial and ulnar type. The radial loop slops toward the thumb, and the ulnar loop slops toward the side of the little finger [1]. Whorls are generally circular or spiral in nature. Arches are mound-like contours, whereas tented arches are like spikes or steeples in appearance at the center. Whorls and deltas provide a direction but they are not unique in general, for unique orientation and position of fingerprint loops are considered. This level of features cannot be suitable for recognizing individuals but can help in narrowing the search. By two singular points, we can figure out another feature like ridge frequency (number of ridges along the line joining two singular points), ridge orientation, etc. Techniques like the Poincare index and Generalized Structure Tensor (GST) are used to identify singular points. Bigun and Mikaelyan [7] have proposed a fingerprint-matching approach by generating a frequency map with the help of a structure tensor. Generalized Hough transform can also be used to find a peek, suggesting the loop position.

Poincare Index. it is the oldest singular point detection method. The Poincare index indicates the amount of angle change along the curve, assuming the curve is closed and in the gradient field of a fingertip [4]. Poincare index P is derived for the path in a vector field, and it is formulated as given in equation (1) where $\theta(x, y)$ describe the angle of the gradient vectors [4].

$$P = \oint \frac{\partial\theta}{\partial x} dx + \frac{\partial\theta}{\partial y} dy = \iint \left(\frac{\partial^2\theta}{\partial x\, \partial y} - \frac{\partial^2\theta}{\partial y\, \partial x} \right) dxdy \qquad (1)$$

Figure 4 signifies the value of Poincare index p for a loop (-2π radians), for a whorl (-π radians), for a regular (non-singular) point (0 radians), and for a delta (πradians).

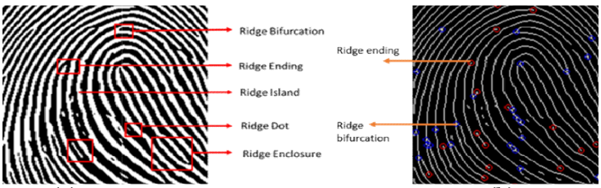


(a) (b) (c) (d)

Fig. 4. (a) Poincare index P = -2π, (b) P = -π, (c) P = 0, (d) P = π for loop, whorl, regular point, and delta respectively [4].

2.2 Level 2

Level-2 features anticipate the properties of the ridges. Properties like ridge type, ridge flow, and deviation of the ridge from its path. These properties are defined using minutiae points, figure 5 demonstrates the type of minutiae points in an enhanced and skeleton image [8]. The most common types of minutiae points are ridge ending, bifurcation, island, scars, and lake [8]. They have highly practiced features in the fingerprint matching system, and it is very tough to rebuild the original fingerprint with minutiae point templates only. Which make them highly efficient for security concern.



(a) (b)

Fig. 5. (a) Minutiae points and [8] (b) ridge-bifurcation and ridge-ending points mined from the corresponding contactless fingerprint.

Ridge ending and bifurcation are the two most common minutiae features considered in fingerprint matching, as demonstrated in Figure 5 (b). To extract minutiae features, a fingerprint image is first transformed into greyscale, and a binary image is attained by the thresholding technique. After that using some morphological operations, a thinned image is achieved. Rutovitz's crossing number technique can be used to extract ridge ending and bifurcation points as explained in figure 6. For CN value 1, the point is acknowledged as the ending point, and for CN value 3 point is bifurcation. The formula of the CN number is [9]:

$$\mathrm{CN} = \frac{1}{2}\sum_{i=1}^{8} |P_i - P_{i-1}| \qquad (2)$$

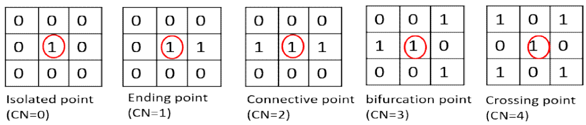


Fig. 6. (a) Crossing number calculation on image for minutiae detection [9].

Accurate minutiae point extraction needs a precise thinning process, which demands high-quality fingerprint images. Because in low-quality images there are several minutiae points extracted, of which only a few are real. Various criteria for validating minutiae points and removing spurious minutiae points (like setting a minimum length for the ridge) are used. Same as singular points, minutiae points direction can also be extracted using a directional field directly or from the thinned image. Which can also be used as a valuable discriminative feature for matching and registering two fingerprint images. Similar to singular points, minutiae points are not sufficient for fingerprint matching. therefore, we can compute another feature like ridge frequency (along the direction of the minutiae point or along-the-line-joining the two minutiae points) and ridge orientation with the help of minutiae points [4]. Level-1 and level-2 features can be used as image alignment tools to register or align input images with stored, before computing other features for fingerprint matching.

2.3 Level 3

Level 3 features involve extracting fundamental information from high-resolution fingerprint images (1000 dpi). This detailed information refers to the pores, ridge units, edge details, scars, etc. as shown in Figure 2 (c) [1]. This information demonstrates the great matching accuracy of partial fingerprint matching, and it is in high demand with high-security level applications. These features are usually employed as additional features to improve the accuracy. Combining these features with Level 1 and Level 2 features displays a boost in accuracy and a reduction in equal error rate. There are two basic approaches used for pore matching. first is the pre-aligned approach used by Jain et al. [10], where the fingerprint image is aligned through minutiae points before matching pores. However, the performance of this method relies on the accuracy of the alignment method. The second approach is direct pore matching [11],[12], where pores are directly matched, usually using an ordered coarse-to-fine fingerprint matching strategy by establishing one-to-one or one-to-many pores' correspondence. Zhao et al. [11] Proposed a one-to-one pores correspondence built on the local patches around the pores and refined the correspondence using Random Sample Consensus (RANSAC).

2.4 Texture-Features

In an image, texture offers us information about the spatial arrangement of the intensity values. It is a feature that partitions the image into regions and classifies them according to the spatial distribution of intensities in the neighborhood.

Local Binary Pattern. in this method, a histogram of the image is created using local patterns based on the gray levels, where the local texture of the image is defined by the bins of the histogram. They are rotational invariant and computationally inexpensive. In this approach image is segregated into different sections and a cell is carefully chosen. This selected cell can be circular or rectangular having (P, R), where P and R are the number of pixels and the radius for the cell respectively [13]. As illustrated in Figure 7, the center pixel is used as a threshold value, and neighboring pixels are altered according to that as 0 or 1 [13]. After this binary value is converted to the corresponding decimal value. After completion, a histogram is created based on 256 bins combined with all pixel values.

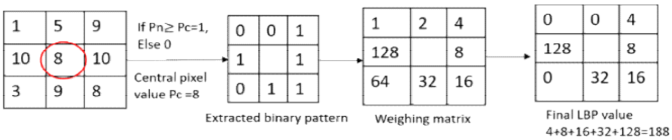


Fig. 7. LBP calculation in greyscale image [13].

Gray-Level Co-occurrence Matrix (GLCM). It is an old texture analysis method. It establishes the relation between two neighboring pixels. How frequently a certain combination of pixels is present in an image for a given direction and distance. For an image, 4 GLCMs are generated at 0°,45°, 90° and 135° with a predefined distance. Figure 8 represents the GLCM formation at 0° with a distance of 1. After creating GLCM statistical features like correlation, contrast, homogeneity, dissimilarity, entropy, and energy are calculated. A feature vector is generated to compare both the input image and stored template for fingerprint matching. Ravinder Kumar et al. [14] used the grayscale cooccurrence matrix to extract second-order texture information. Cevik et al. [15] proficiently completed a comparative fingerprint-matching analysis based on both GLCM and DWT alone and combined.

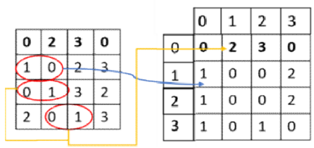


Fig. 8. GLCM formation [16].

2.5 Frequency Features

Feature-based matching performed well on fingerprint images having non-linear distortion, but not on poor quality images or weak fingerprint impressions (because of skin allergic on the fingertip, rough fingertip, and dry fingertip). Frequency features can perform well on low-quality fingerprint images. Frequency features involve phase and amplitude information of fingerprint images in the frequency domain. For comparison two input images are overlaid over each other to compute the correlation between them. Frequency features comprise a correlation for different orientations between pixels [2]. Numerous methods are used like 2D discrete Fourier transform for Phase-based matching and Fourier-Mellin transform for fingerprint matching using frequency information.

Phase-Only Correlation. Phase-only correlation employs Discrete Fourier Transform (DFT) to find phase information, which is further used as a measure for translational shift in image registration and as a match score for biometric recognition. Ito and Aoki [2] used the BLPOC (band-limited phase-only correlation) successfully on multi-biometric recognition using phase information. The only problem with BLPOC is the non-linear deformation of the image because we are using information on phase for the complete image [2]. To reduce this BLPOC can be combined with Phase based matching.

Fourier-Mellin. Another approach using the frequency feature is the Fourier-Mellin transform (FMT). It translates the rotational and scale information of the query image into a translational shift in the output image. Using phase correlation between two transformed images, rotation and scale changes can also be estimated [3]. So, alignment is accomplished by phase correlation and FMT, and later for matching BLPOC method is implemented. Though BLPOC improves the accuracy of fingerprint matching, it will be time-consuming for large databases. Because it will repeat the process of image alignment and phase feature extraction for each image of the database. Therefore, another fast method is suggested where matching is performed directly only on the low-frequency bands of the phase. These features are termed as Fourier Mellin Band Limited phase (FMBLP) [3].

2.6 Deep Features (Global Features)

Deep learning-based approaches have been developed in recent years, they automatically train the feature extractor to extract deep features. To extract them various convolutional-neural-network (CNN) models are employed. These features are mined automatically to perform a specific work, making them very effective. Therefore, deep learning-based models outperform the manually extracted (Handcrafted) features. They are good only for the task they are trained for, and there is no power over the model on what features it is extracting. So, in numerous situations, they are good only for classification not for the real-world problem. To overcome this problem combination of deep and handcrafted features has been proposed by many researchers [17][18]. Thus, a hybrid feature vector is formed which can hold more information than a single feature and have strong discriminating power. Many approaches like Lin and Kumar [19] practiced the CNN model with features like minutiae and core points, and Malhotra et al. [20] used deep features. Chowdhury and Imtiaz [21] accomplished a detailed study of the deep learning approaches for contactless fingerprint recognition. They enlightened the basic architecture of the deep learning model and their stages of pre-processing, feature extraction, and matching with its usability and possible downsides. These models have shown development in contactless fingerprint matching with some challenges like the time needed in preprocessing and speed of feature extraction for improving the accuracy of the identification.

3. Comparison Among Approaches

Lin and Kumar [19] proposed a multi-Siamese Convolutional neural network for contact-based and contactless fingerprint matching. Along with minutiae features, the core point is merged to train the multi-Siamese CNN model. It outperforms many CNN-based models but the complexity is high. Cevik et al. [15] expertly accomplished a comparative fingerprint-matching analysis based on both GLCM and DWT alone and combined. A combination of both GLCM and DWT has shown promising results.

Lin and Kumar [22] addressed sensor interoperability in contact-based and contactless fingerprint matching. Although, it is a challenging problem, then again Fingerprint information about texture, depth, and shape is learned from the multi-view CNN. The proposed approach shows significant improvement, but still, an equal error rate can be improved further. The author used minutiae features for the alignment of the fingerprints and an additional feature, minutiae-related ridges is used for matching. Takahashi et al. [23] presented a CNN-based architecture that incorporates texture, frequency, and minutiae features for fingerprint recognition. They achieved better accuracy than any other conventional and VeriFinger methods. Malhotra et al. [20] extracted features using a Deep-Scattering Network (DSN), and to validate the fingerprints Random Decision Forest approach is practiced. Steven et al. [24] proposed a deep neural network model 'deep-print' for contact-to-contactless fingerprints. It has an extensive pre-processing pipeline with enhancement and segmentation. The final match score is achieved by computing the match score as a weighted fusion.

Liu et al. [25] improved the recognition accuracy of contactless fingerprint matching using an image quality evaluation algorithm based on the SURF and Roi frequency domain. Which is used to evaluate the quality of target ROI using frequency domain intensity from local and global levels. Score-level fusion is performed to achieve improved accuracy. Rajaram et al. [26] proposed a CNN-based Child recognition system “Child-CLEF” for contactless fingerprint matching. A novel fusion score is obtained using wavelets, and minutiae matching with the deep-learning method. Minutiae features are extracted using Child-CLEF net and matching is performed using the BOZOROTH3 algorithm. For this experiment child fingerprint dataset is generated and the PolyU fingerprint dataset is also used to achieve 98.46% accuracy with 1.99% ERR. On the other hand, Guruprasad et al. [27] employed a score fusion technique for better accuracy using wavelets with deep-learning and minutiae models. Computation is operative in this approach because the parameters used in calculation are fewer. They have suggested attempting different wavelets and fusion techniques to improve the accuracy.

All the approaches above combined two or more features to improve the accuracy. Therefore, combining deep learning approaches with handcrafted features is suggested to create a hybrid feature vector. Table 2 represents the approaches used for fingerprint matching in combination with different features (Texture, minutiae, frequency, and deep features) to form a hybrid approach with performance evaluation.

Table 2. Related approaches for fingerprint matching.

Approach	Features	Method	Accuracy	Remarks
Lin and Kumar 2017 [19].	minutiae and core point.	Multi-Siamese CNN	91.61%	The complexity of the framework is high; the result is good but still below expectations.
Cevik et al 2018 [15].	Texture features	GLCM and DWT.	93%	Results are good but as the DWT compression level increases, the result of identification decreases.
Lin and Kumar [22] (2018)	Minutiae, ridge properties	2-channel Multi-view CNN	96.25%	Developing a partial 3D fingerprint database in a realistic environment is highly desirable.
Takahashi et al. 2020 [23].	Texture, minutiae, and frequency.	CNN	98%	Achieved higher accuracy than conventional methods.
Malhotra et al. 2020 [20].	Deep features	DSN and RDF	97.51%	DSN+RDF is supported by a segmentation and enhancement framework.
Steven et al. 2021 [24].	Minutiae and texture features	Deep-print CNN and Verifinger 12.0 SDK	98.3%	Extensive preprocessing consists of segmentation, Enhancement, normalization, and deformation correction.
Liu et al [25] (2023)	Frequency domain intensity	SURF and ROI frequency		Contactless fingerprint and palmprint fusion are used for recognition.
Rajaram et al. [26] (2023)	Minutiae, Texture	CNN based Child-CLEF	98.46%	Building a network independent of fingerprint size is more feasible. So, patches should be used instead of the whole fingerprint.
Guruprasad et al. [27] (2023)	Texture and Minutiae	Wavelets, deep learning, minutiae	98.1%	Performed better than simple CNN, different wavelets should be tried.

4. Evaluation and Result

All the features explained above have their benefits and shortcomings. The accuracy of matching fingerprints decreases in level-1 and level-2 features as the quality of fingerprint images decreases. level-3 features comprise ridge details and pores, for which quality images are required to exhibit high accuracy in matching. The overall evaluation of the features studied in this paper is demarcated in Table 3 with their pros and cons.

Table 3. Evaluation of features.

Features	Type of features	Method of extraction	Pros	Shortcomings
Level 1	Singular points	Poincare index, GST, and Hough transform	Easily extractable	Not sufficient to uniquely identify or recognize.
Level 2	Minutiae points	Crossing number	Easily extractable, determine the uniqueness of a fingerprint image.	Missing minutiae and false minutiae degrade the quality of matching.
Level 3	Pores and ridge-type	--------	High recognition accuracy	Pore's information is tough to extract.
Texture	Statistical features	LBP, GLCM, etc.	Good accuracy on low-quality images. It is possible to reconstruct the original image	Slow down the recognition speed, especially on large-scale database
Frequency	Amplitude and Phase	POC, BLPOC, FMT	Matching of low-quality images is also possible	They cannot handle nonlinear deformation, and time-consuming
Deep features	Global features	Deep neural network, CNN	Outperform handcrafted features.	They are good only for the task they are trained for.

Contactless and contact-based fingerprint have their limitations. Therefore, selecting the features to be studied for matching is vital, because one feature alone won't give good recognition accuracy. So, it is crucial to combine two or more features in a well-organized way to get a highly efficient fingerprint-matching system. Deep-learning models have shown promising advancement in the performance of contactless fingerprint matching. though, some challenges are present in these methods, such as speed of feature extraction and time required in the processing of input image.

5. Discussion

As explained earlier level-1 (singular points) and level-2 features (minutiae points) are not sufficient for uniquely identification. But they can be used to create some new features for fingerprint matching, like ridge frequency along the line of direction of feature point, or ridge count in the line joining two singular or minutiae points. Both minutiae and singular features can also be used for the alignment of fingerprint images, before extracting some other features for matching. Therefore, singular and minutiae features can be used as a piece of vital information to extract other descriptive features. Texture, minutiae, and frequency features (handcrafted features) can also be combined with deep learning methods to generate hybrid parameters for fingerprint matching. Deep-learning models surpassed many handcrafted feature extraction models in performance, but the speed of such models is low and good for classification only. So, to resolve this problem handcrafted features are used in combination with deep-learning models by many researchers as shown in Table 2.

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